Predicting fire-regime responses to climate change over the past millennium: Implications of paleodata-model comparisons for future projections of fire activity

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Awards: ARC-1023477, ARC-1023669

Award: 14-3-01-7

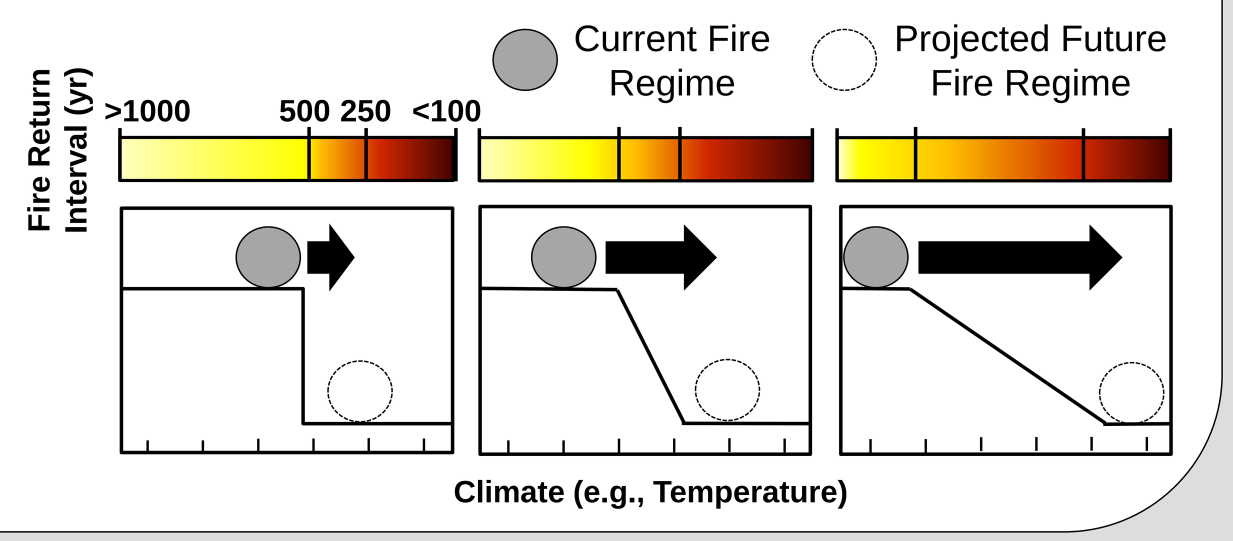
1. Motivation and approach

Statistical models using historical observations are a critical tool for anticipating future fire regimes[1]. A key uncertainty with these models is the ability to project outside the range of historical observations[2], often done when making future projections. Here we investigate how nonlinear, threshold relationships between climate and fire contribute to uncertainties in projections of fire activity outside the range of historical observations, by applying a set of statistical models to predict fire activity over the past ~1100 years. We ask two key questions:

Questions

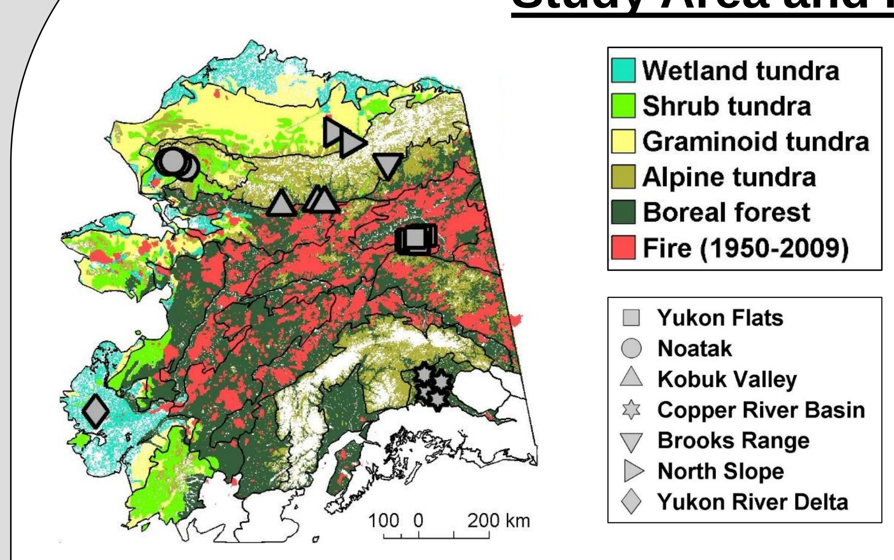
(1) How do nonlinear, threshold relationships impact our ability to predict fire regimes?

(2) What are the implications for accurately predicting future fire regimes?

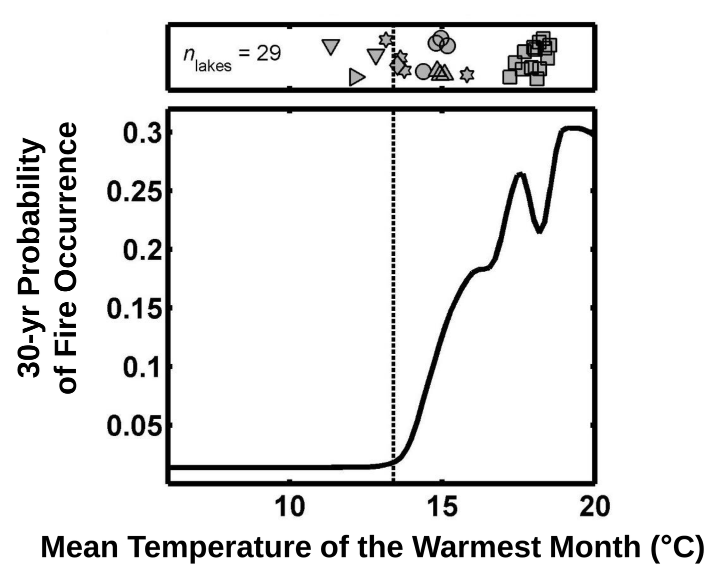


2. Methods

Study Area and historical models

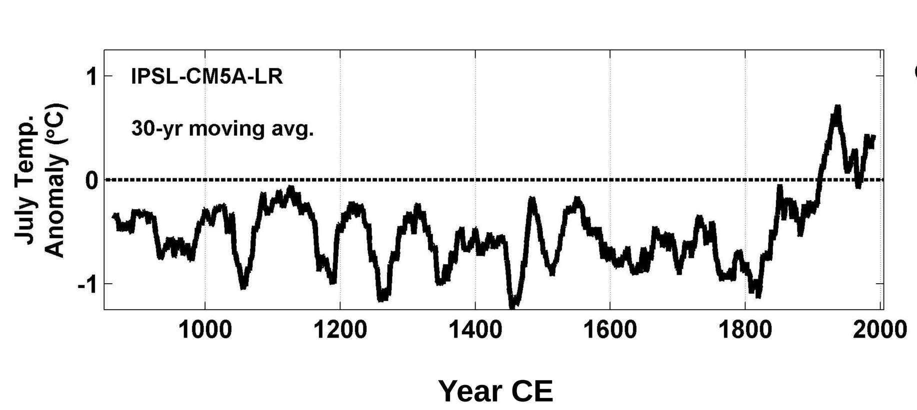


Study area in Alaska, including historical fires (1950-2009), modern vegetation, and locations of paleofire records (n = 29).



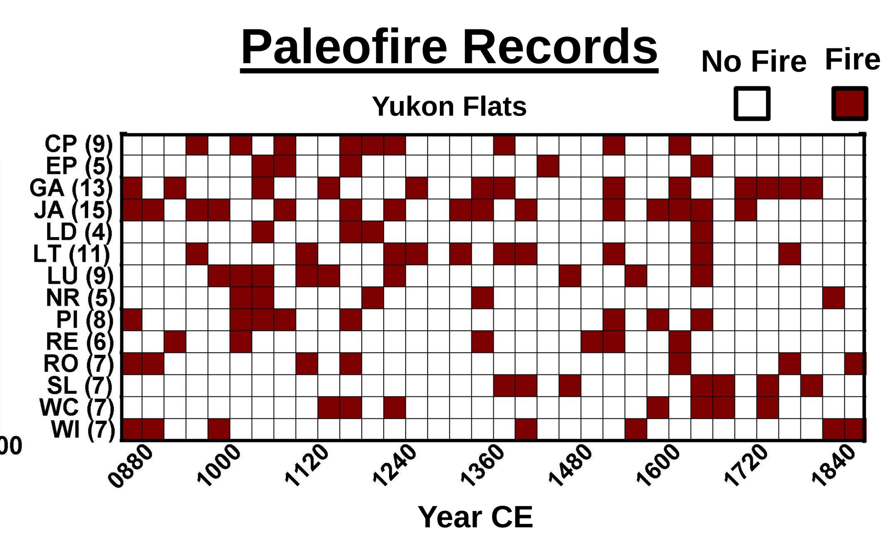
Climatic locations of paleofire records (top) and predicted probability of fire from statistical models based on historical fire-climate relationships[3].

Global Climate Models (GCMs)



Downscaled[4] GCM data[5] were used to drive statistical models over the past 1000 years.

Paleofire Records



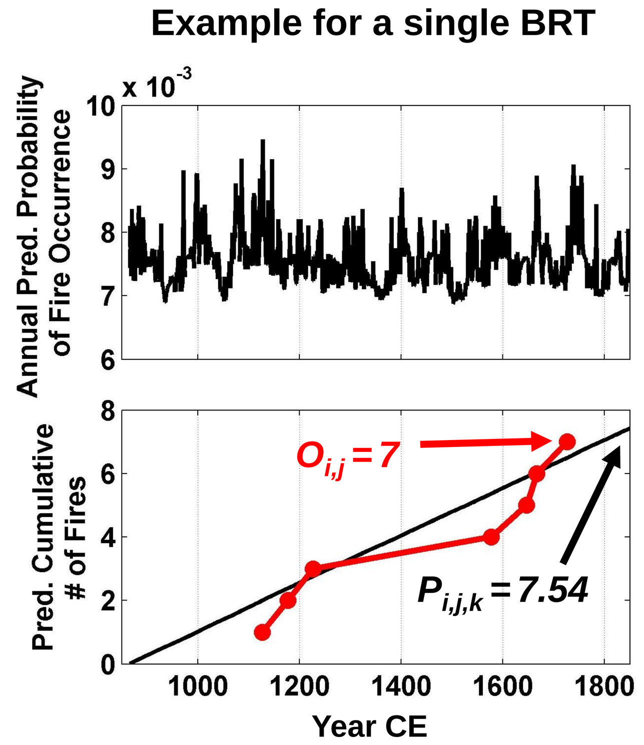
We used 29 paleofire records[6,7,8,9,10] which identify fire events with statically significant charcoal peaks, to quantify model performance over the period 850-1850 CE.

Quantifying model performance

To evaluate how well historical models predicted fire regimes for the past 1000 years, we used downscaled GCM climate data to drive 100 boosted regression tree models (BRTs)[11], which predict the 30-yr probability of fire occurrence. We quantified model performance using a standardized error measure ($E_{i,j,k}$), where i represents ecoregion, j represents a lake within the i^{th} ecoregion, and k is one of 100 BRTs. Observed (O) and predicted (P) values were converted to mean fire return intervals (e.g. $n_{yr} / P_{i,j,k}$).

$$E_{i,j,k} = \frac{P_{i,j,k} - O_{i,j}}{\overline{O}_{i,\bullet}} \times 100$$

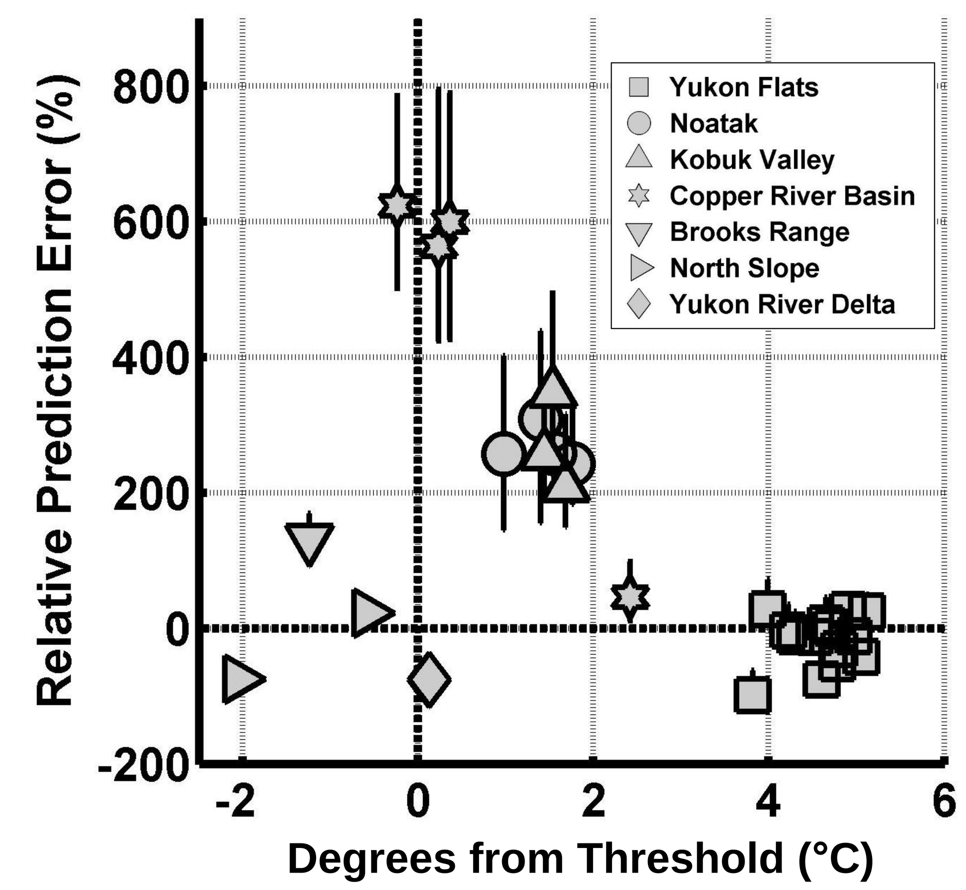
Example for a single BRT



3. Paleodata-model comparisons

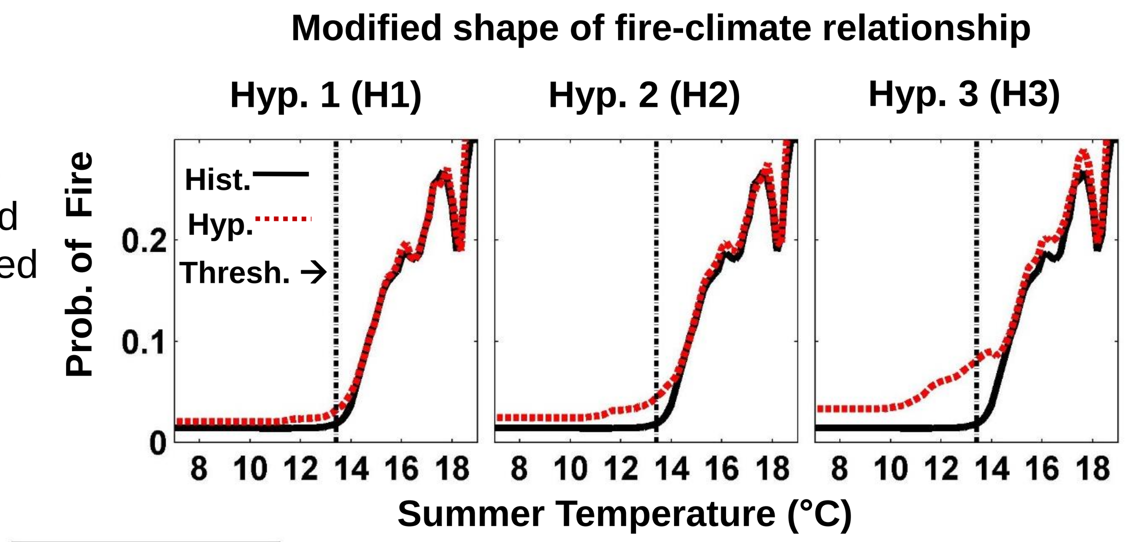
Comparing predictions and paleofire reconstructions

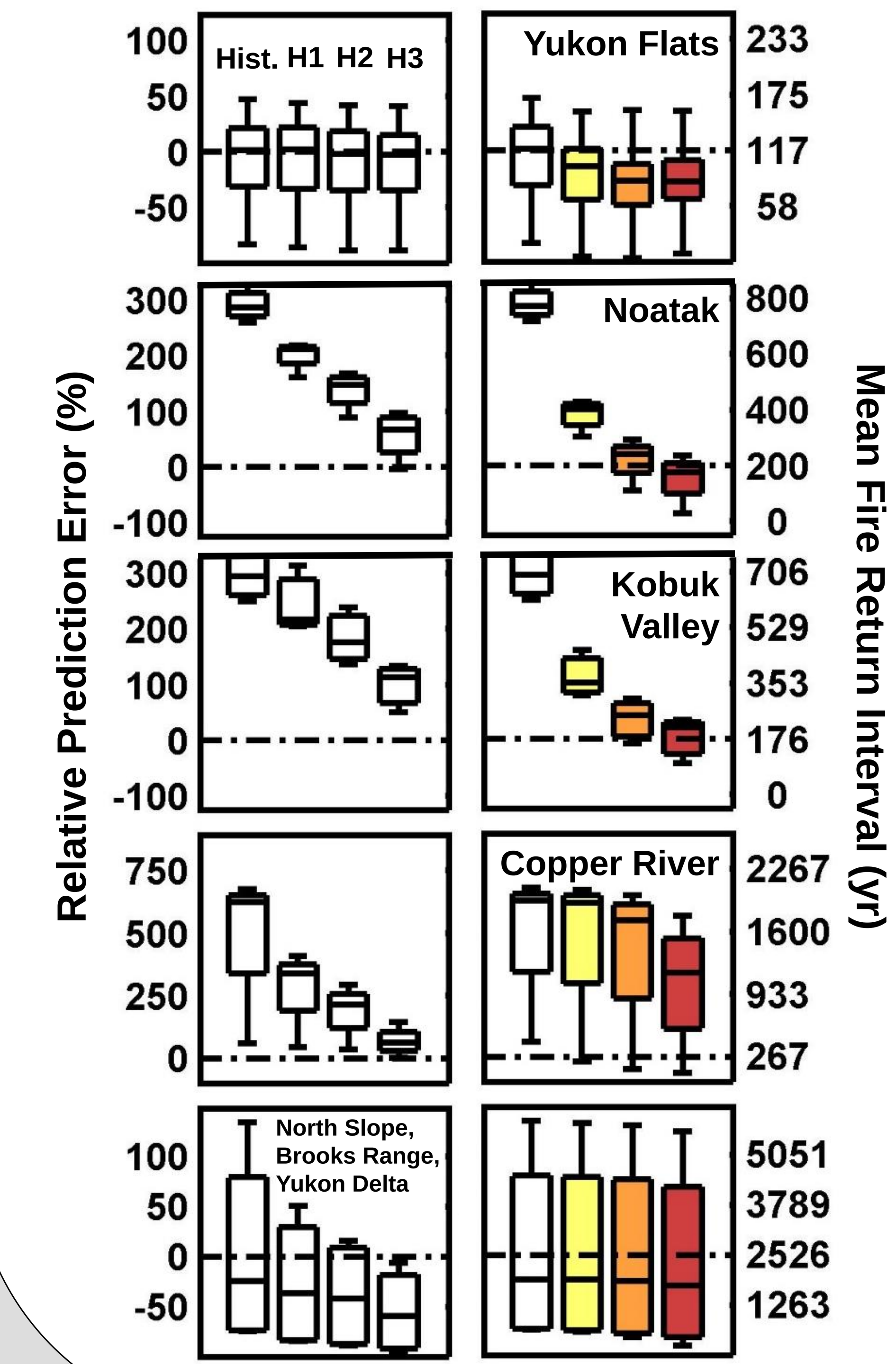
The accuracy of model predictions for the past millennium varied significantly depending on how close a site was to observed climatic thresholds. Prediction errors were low in regions further away from the 13.4 °C threshold (i.e., Brooks Foothills and Yukon Flats) and highest in regions close to this threshold.

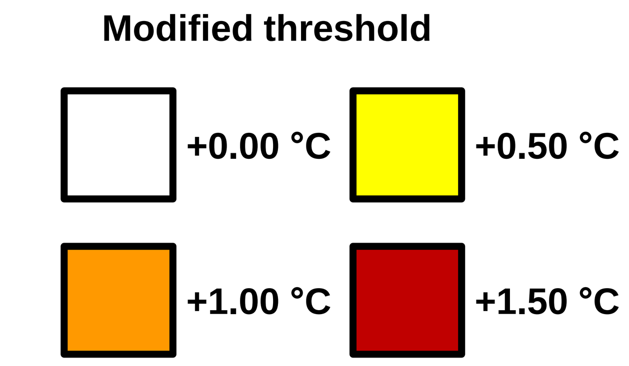


Testing different fire-climate relationships

To understand the sensitivity of predictions to the shape of threshold relationships, we modified historical fire-climate relationships:







Modifying threshold locations had a significant impact on predictive performance in regions near climatic thresholds.

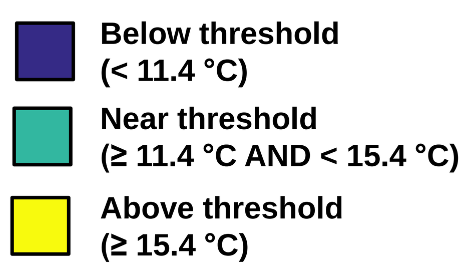
Modifying the shape of the fire-climate relationship had less impact on prediction accuracy than modifying threshold values. The most extreme modification (H3) resulted in the largest changes, specifically in regions at or below the 13 °C threshold (e.g., Copper River Basin, North Slope, respectively).

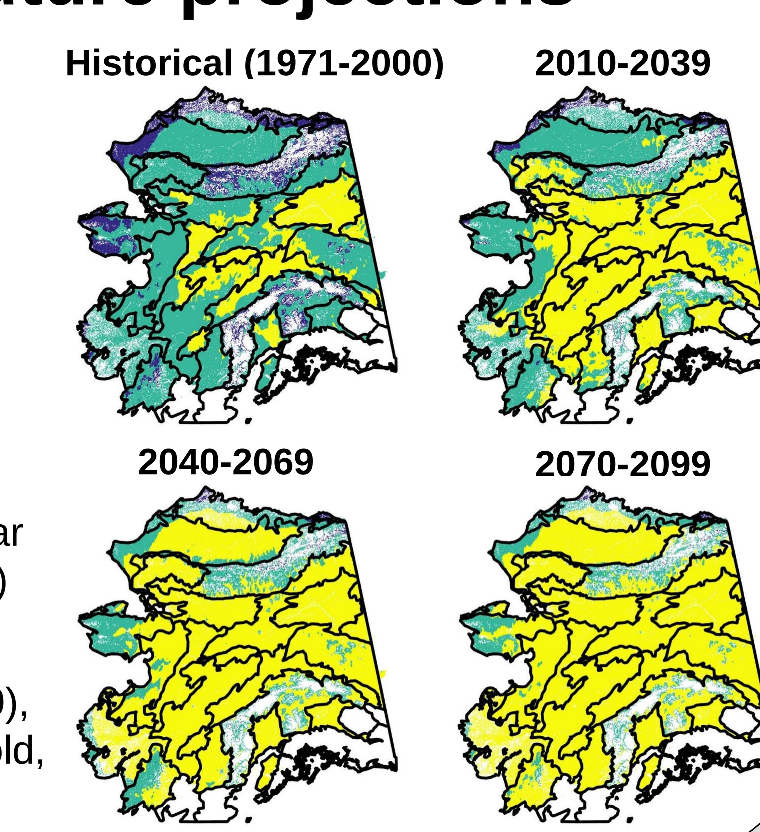
Conclusions

- ❖ **Prediction uncertainty is highest for regions near climatic thresholds.**
- ❖ **Significant uncertainty can arise from even small changes in fire-climate relationships.**
- ❖ **Threshold-driven uncertainty will be most prominent in tundra and forest-tundra regions during the early 21st century.**

4. Implications for future projections

To understand how threshold-related uncertainty may impact future projections, we classified locations in Alaska based on the proximity to the observed temperature threshold (13.4 °C).





Most tundra and the forest-tundra regions lie near the temperature threshold, currently (1971-2000) and in the near future (2010-2039).

During the mid- and late-21st century (2040-2100), most of Alaska exceeds the temperature threshold, surpassing this area of high uncertainty.

References

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